MLCC_SXC

MACHINE LEARNING
CRASH COURSE

FEATURE CROSSES AND REGULARIZATION

Week 2

- Jimut Bahan Pal
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TRAINING AND TEST SET

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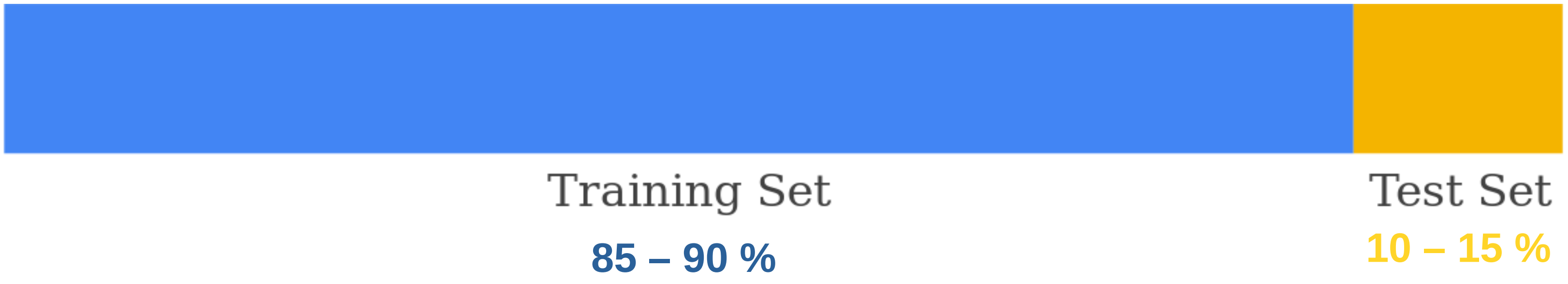

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TRAINING AND TEST SET

Some points to keep in mind while training the model

- The larger the training set, the better the model

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- The larger the test set, the larger the confidence in the evaluation matrix

- DONOT TRAIN ON THE TEST DATA

    - If you find surprisingly low losses make sure to check if you have trained on the test data or have forgot to randomize the data.

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TRAINING AND TEST SET

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- It may happen that you are training on the dataset which follows the same pattern, like training the whole dataset on winter values and validating on summer values, this might result in errors, make sure to avoid such errors so that the model predicts well for all values.

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- Test set is large enough to yeild statistically meaningful result.

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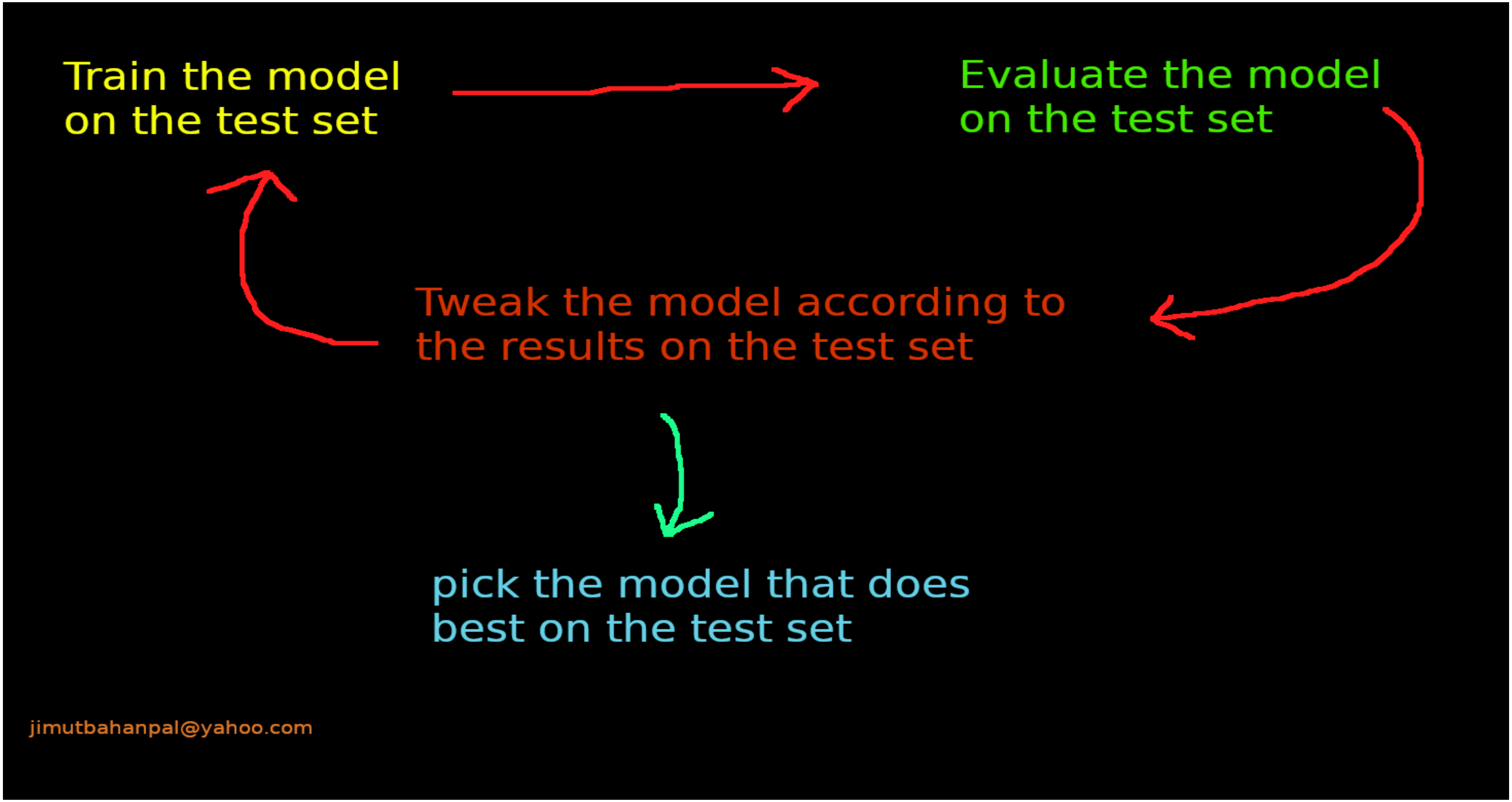
TRAINING AND TEST SET

WORK FLOW



TRAINING AND TEST SET

WORK FLOW - The iterative method

We have trained the model on the training data and now we will test the model on the test data and observe the matrix. We will tweak some settings, maybe the learning rate and try again. We will see if we could try to improve the test set accuracy.

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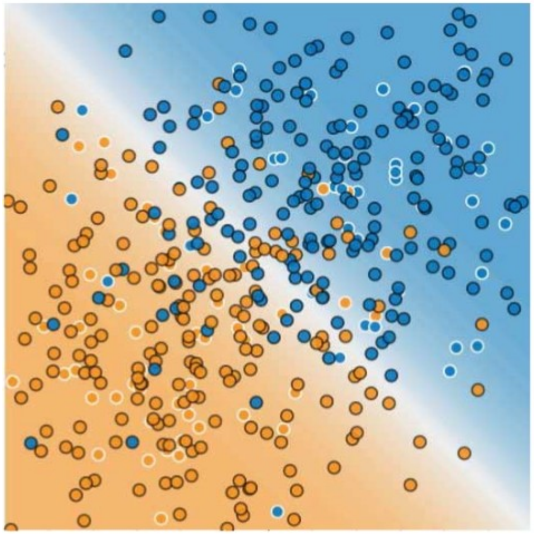
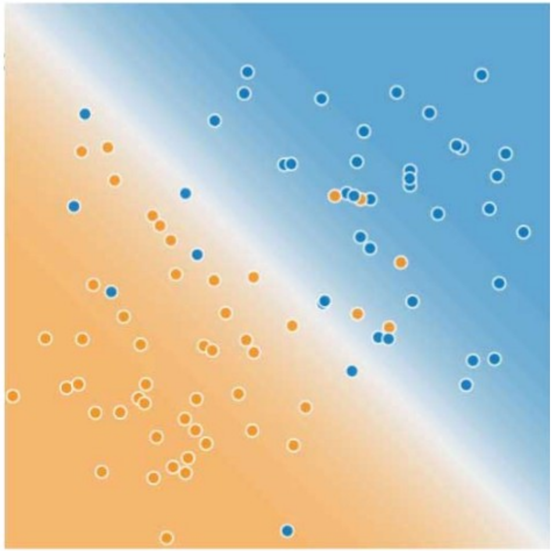
Maybe add some more features in them, maybe take some features out and keep iterating till we find the best iterative model that can predict best in the test set matrix.

TRAINING AND TEST SET

Example of a classification problem



Training Data



Test Data

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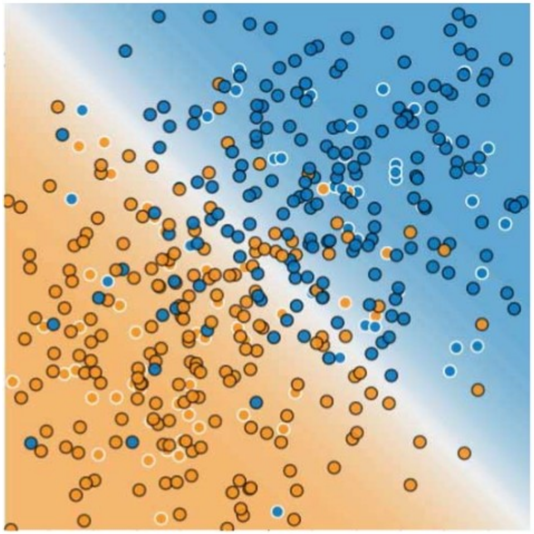

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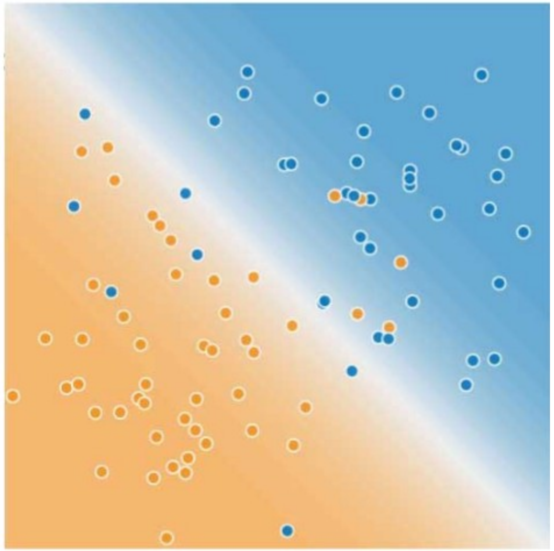

Test Data

From this example we see that the model is not perfect, but it works well on the test data. This model may result in wrong predictions for some exceptional values but it's doing perfectly fine since the training set also have a few erroroneous exceptional data, and it is not overfitting the data!

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VALIDATION

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ARE THERE SOME PROBLEMS ?

VALIDATION

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that’s too is bad

But we can do something :D

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We will partition the training set into another part known as validation set, which results to reduce any case of overfitting by any chance. Use validations to evaluate results from the training set. Use the test set to double check your evaluation after the model has passed the validation set

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70 – 80 % **10 – 15 %** **10 – 15 %**

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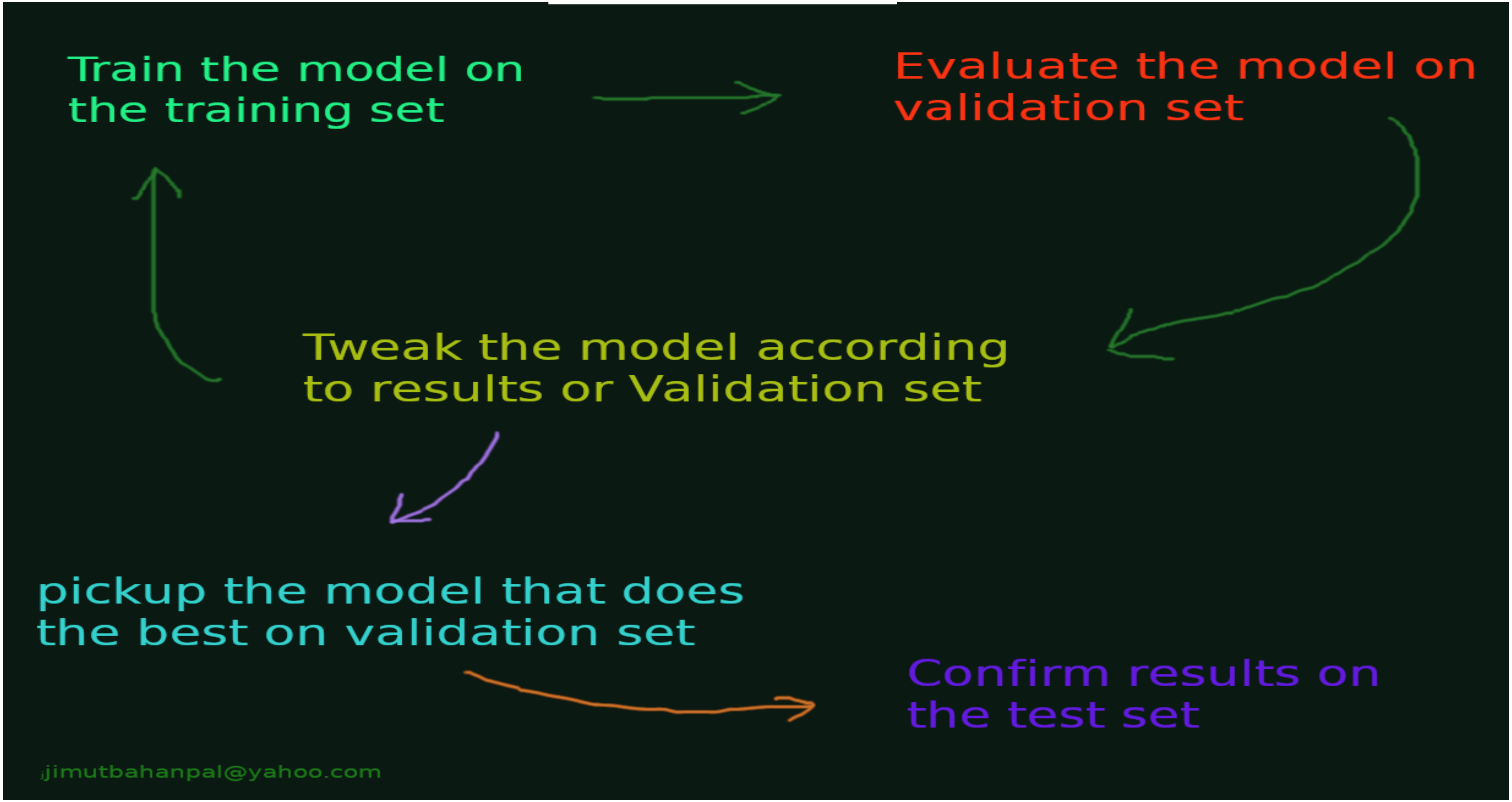

REPRESENTATION

Feature Engineering

Traditional programming focuses on code, but ML engineers focus on representation. The way developers hone a model is by adding and representing features. When we work with ML, the features doesn’t come as feature vectors in formatted options, instead as database records or protocol buffers.

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Role of a ML engineer

The ML engineer takes data from heterogenous sources and create feature vectors from it. The process of extracting features from raw data is called as feature engineering. This is about 75% of the time spent by a ML scientist/Engineer.

REPRESENTATION

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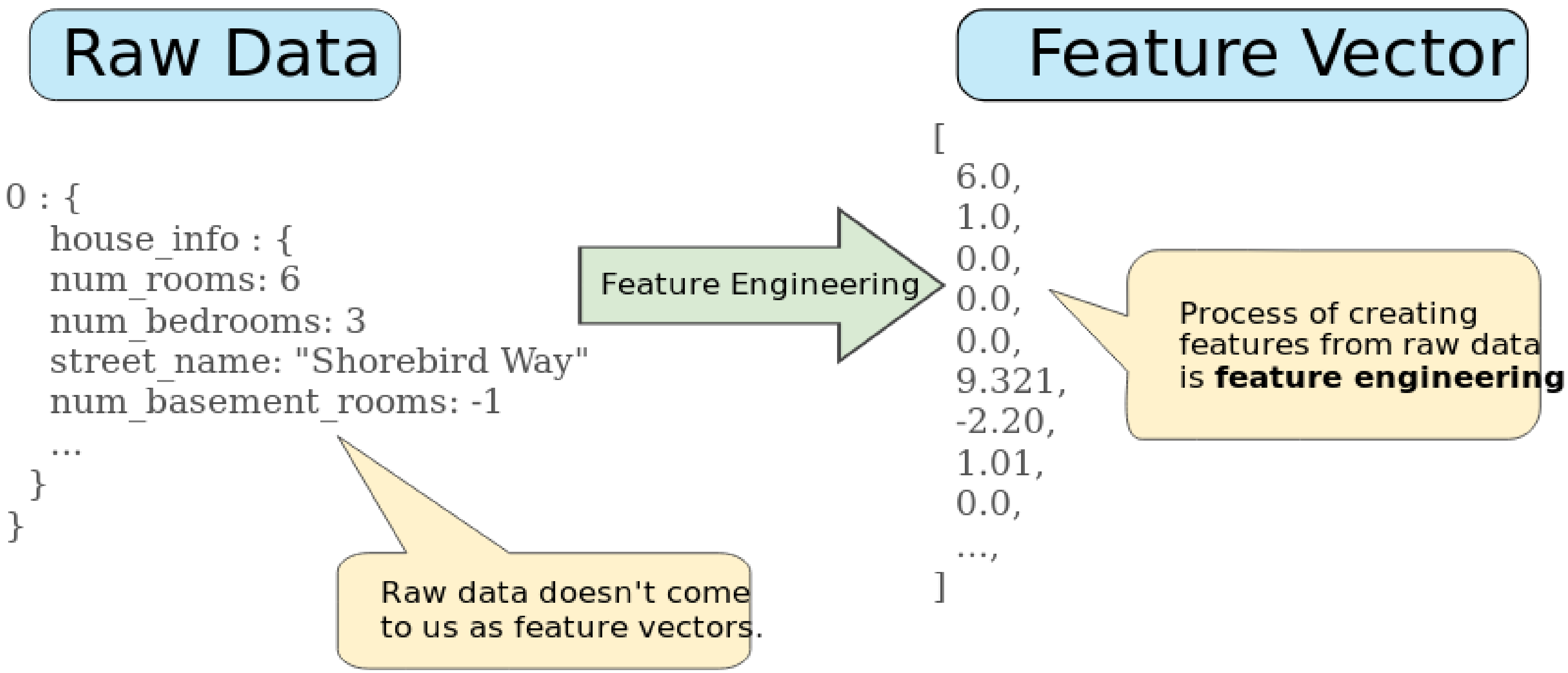

Feature engineering maps raw data to ML features.

Mapping numeric values

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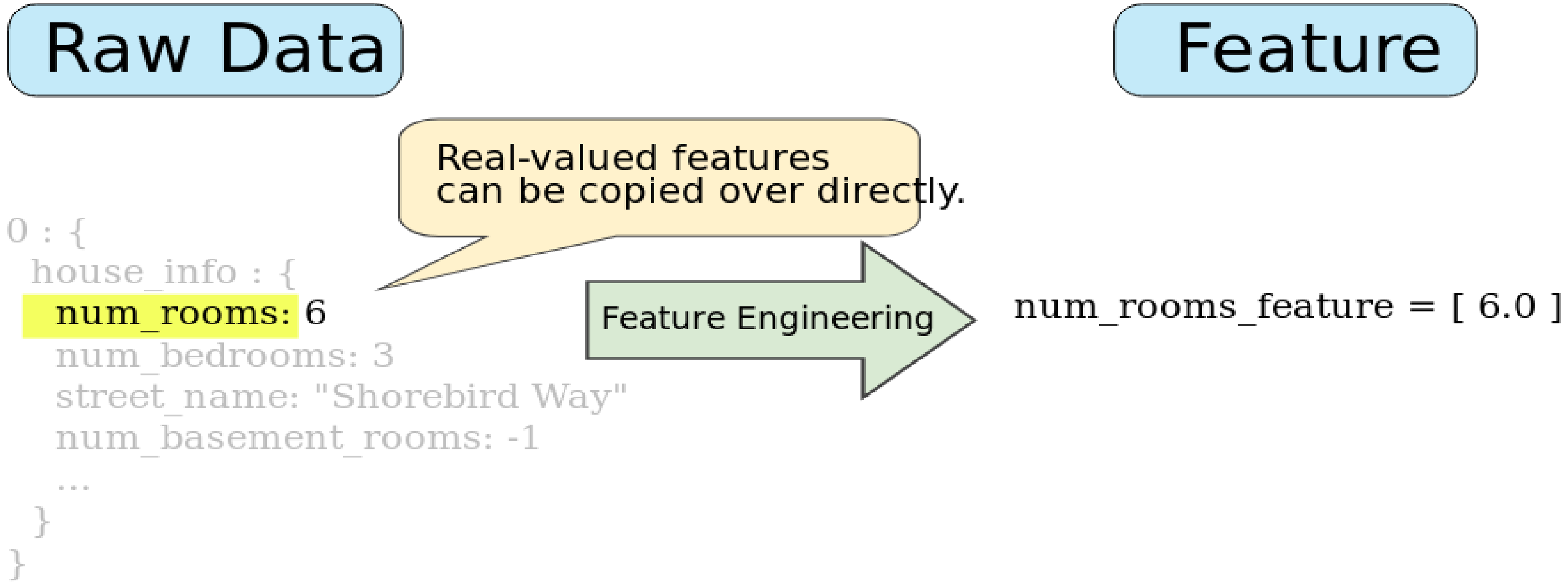

Mapping integer values to floating-point values.

REPRESENTATION

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- **For values that apply to the example, set corresponding vector elements to 1.**

- **Set all other elements to 0.**

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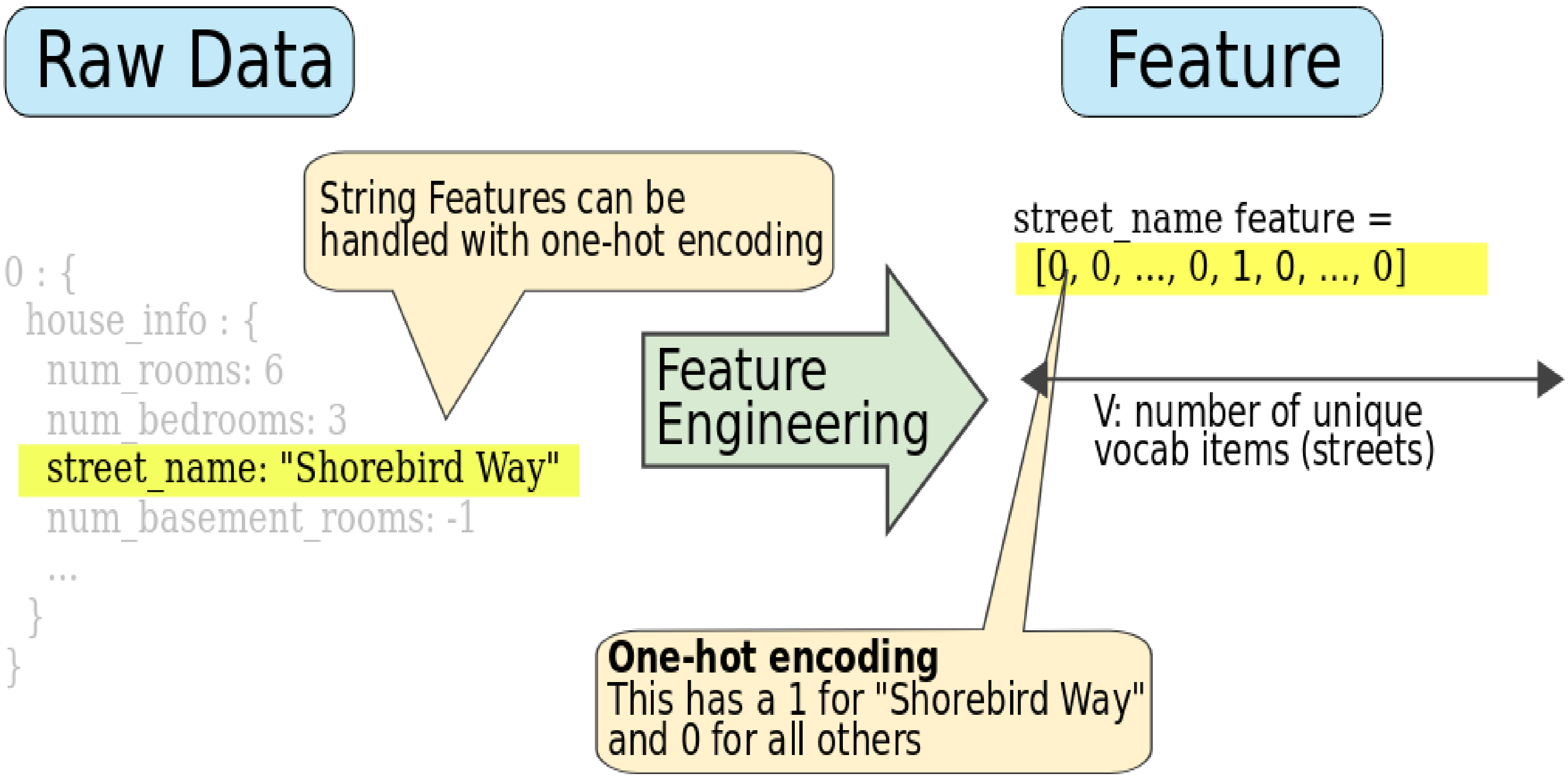
Mapping ‘street’ via One hot encoding



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REPRESENTATION

Qualities of Good Features

- **Avoid rarely used discrete feature values : the feature should be non-zero atleast a handful of time in our dataset. Doing so enables a model to learn how this feature value relates to the label. That is, having many examples with the same discrete value gives the model a chance to see the feature in different settings, and in turn, determine when it's a good predictor for the label.**

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- **Account for upstream instability : the definition of a feature shouldn't change over time.**

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- Scaling feature values : Scaling means converting floating-point feature values from their natural range (for example, 100 to 900) into a standard range (for example, 0 to 1 or -1 to +1). If a feature set consists of only a single feature, then scaling provides little to no practical benefit. If, however, a feature set consists of multiple features, then feature scaling provides the following benefits :

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- **Helps the model learn appropriate weights for each feature. Without feature scaling, the model will pay too much attention To the features having a wider range.**
- **Avoids the NaN trap in which one number exceeds the floating point precision limit during training, so other numbers on multiplication too becomes NaN.**

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- Handling extreme outliers : Suppose there is a dataset for values of rooms per houses, and in that cluster, some celebrity's house's data is also included. So on an average if the no. of rooms be 8-10 the celebrity may have 30-40, now that will create a problem and be outlier when we plot a nox plot. It is better to remove those values from the cluster since the model will learn to predict abnormal values for normal people.

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  Bad feature values: For example, someone typed in an extra digit, or a thermometer was left out in the sun.

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